The Effects of Ambient Air Pollution on School Absenteeism Due to Respiratory Illnesses

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We investigated the relations between ozone (O_3), nitrogen dioxide (NO_2), and respirable particles less than 10 μm in diameter (PM_{10}) and school absenteeism in a cohort of 4th-grade school children who resided in 12 southern California communities. An active surveillance system ascertained the numbers and types of absences during the first 6 months of 1996. Pollutants were measured hourly at central-site monitors in each of the 12 communities. To examine acute effects of air pollution on absence rates, we fitted a two-stage time-series model to the absence count data that included distributed lag effects of exposure adjusted for long-term pollutant levels. Short-term change in O_3, but not NO_2 or PM_{10}, was associated with a substantial increase in school absences from both upper and lower respiratory illness. An increase of 20 ppb of O_3 was associated with an increase of 62.9% [95% confidence interval (95% CI) = 18.4–124.1%] for illness-related absence rates, 82.9% (95% CI = 3.9–222.0%) for respiratory illnesses, 45.1% (95% CI = 21.3–73.7%) for upper respiratory illnesses, and 173.9% (95% CI = 91.3–292.3%) for lower respiratory illnesses with wet cough. The short-term effects of a 20-ppb change of O_3 on illness-related absenteeism were larger in communities with lower long-term average PM_{10} [223.5% (95% CI = 90.4–449.7)] compared with communities with high average levels [38.1% (95% CI = 8.5–75.8)]. Increased school absenteeism from O_3 exposure in children is an important adverse effect of ambient air pollution worthy of public policy consideration. (Epidemiology 2001;12:43–54)

Keywords: air pollution, ozone, respiratory illnesses and children, school absenteeism.

Ambient air pollutants including ozone (O_3), nitrogen dioxide (NO_2), and respirable particles less than 10 μm in diameter (PM_{10}) contribute to the occurrence of respiratory symptoms and diseases including increased occurrence and severity of symptoms, transient changes in lung function, and increased respiratory infections, more visits to physicians and emergency rooms and increased hospital admissions, and changes in lung function and increased mortality.[1–5] Consideration of a broader group of outcomes, such as school absenteeism, provides a more comprehensive assessment of the adverse impact of ambient air pollution.[6,7]

Illness-related school absenteeism is an important but insufficiently studied outcome in children, a group identified as especially sensitive to the adverse effects of ambient air pollution.[8] Illness-related absences are common events that represent a broad spectrum of morbidity from mild transient illnesses to the most severe and prolonged illnesses that require emergency room visits or hospital admissions.[9] Although most absences are associated with illnesses at the low end of the morbidity spectrum, an absence indicates an illness of sufficient severity to affect the child's daily functioning, as well as child and family coping strategies.[9–13]

Population-based studies show that absence rates vary by school, age, grade, and gender, and are affected by family structure, function, and other social factors.[14,15] Although the non-health-related influences on absenteeism limit its usefulness as a measure of the adverse effects of air pollution, the majority of school absences are illness related and attributable to either respiratory infections or gastroenteritis, suggesting that illness is the dominant factor for school absenteeism.[10,14] Because the

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effects of air pollution on school absences are likely to be due to increases in respiratory illnesses, respiratory illness-related absenteeism can be an important and relatively specific integrative outcome for the assessment of the effects of air pollution on children.

Most research on the effects of air pollution on children's health has focused on self-reported symptoms, indices of respiratory infections derived from clinical visits, medical records reviews, and lung function as outcome measures.[6,16] Few studies have examined the effects of ambient air pollution on school absenteeism, and none has examined the effects on respiratory-related absences in school-aged children residing in communities with large variations in pollutant levels.

The Children's Health Study (CHS) offers an opportunity to investigate the effects of three ambient pollutants, O_3, PM_{10}, and NO_2, on school absenteeism with a focus on respiratory illness-related absences.[17] We conducted a substudy within the CHS cohort, the Air Pollution and Absence Study, and examined data on type-specific absence incidence collected by an active surveillance system for a cohort of 4th-grade school children 9–10 years of age who attended schools in the 12 CHS study communities during January through June 1996.

Subjects and Methods

Study Design

The CHS is a 10-year longitudinal study that includes school children who reside in 12 communities within a 200-mile radius of Los Angeles that were selected to represent the broadest range in concentration of the ambient pollutants of interest. Details on the design, site selection, subject recruitment, and assessment of health effects are reported elsewhere.[17] In this report, we focus on school absences among 2,081 children in the 4th grade during the first 6 months of 1996.

Participant Characteristics

Sociodemographic information, indoor exposures, and medical histories were obtained from questionnaires completed by parents or guardians at study entry in the fall of 1995. Environmental tobacco smoke (ETS) exposure was classified as exposure to a current household smoker or not. The subset of participants with asthma was defined using parent-reported history of physician-diagnosed asthma. Children with wheezing were defined as having any lifetime history of wheezing. Information regarding the number of hours spent outdoors over a 1-week period was collected by self-administered questionnaire. Children were stratified into "more outdoors" or "less outdoors" groups on the basis of whether they were above or below the median number of hours spent outside (11.25 hours).

Absence Surveillance

We collected school absence reports from the 27 elementary schools attended by the newly recruited 4th-grade children for the period January 1 through June 30, 1996. Of the 2,081 children in the 4th-grade group, 2,068 were eligible for the absence surveillance because they were enrolled in the CHS at the beginning of the surveillance period. Of these 2,068 children, we excluded 135 from the analysis for the following reasons: 32 withdrew from the study, 90 changed schools during the study period, and 13 did not have absence data because of administrative errors.

Daily absence information was collected using two methods depending on school confidentiality policies. In 12 schools, attendance reports for entire classrooms were collected, and study staff identified absences for participating students. In the remaining 15 schools, school staff members supplied subject-specific absence reports based on lists of subjects provided to them at the beginning of the surveillance period. Study staff requested that absence reports be completed every 2–4 weeks, with the interval depending on the availability of personnel and electronic data systems at individual schools. We defined an absence as a day or an adjacent series of school days in which a participant did not attend school when the school was in session. Over the period of study, we ascertained 8,971 absences.

We established an active surveillance system to collect information about the reasons for absences; we categorized absences as illness-related and non-illness-related (these included injuries) and classified illness-related absences into gastrointestinal (GI) and respiratory categories. School reports classified absences with nonstandard codes including indicators for non-illness-related absences. Non-illness-related absences were not investigated by telephone interviews. Using school reports, study staff assigned daily absence reports to one of two categories: (1) non-illness related and (2) potentially illness related. To ensure adequate parental recall of events associated with the absence of interest, interviews were conducted only for absences that were reported within 4 weeks of occurrence. Of the 3,294 absences reported within 4 weeks, 536 were classified as non-illness absences on the basis of school reports, and 2,758 absences required telephone follow-up.

Telephone interviews were conducted in English or Spanish by trained interviewers using a standardized protocol. Parents were contacted after each absence that was reported within 4 weeks to inquire whether the absence was illness related and if so, what the symptoms were; what the physician diagnoses were, if any; and what medications were used for the reported illness. The interviewers used a list of symptoms to categorize respiratory illnesses (runny nose and sneezing, fever, sore throat, cough, wet cough, dry cough, earache, wheezing, and asthma attack) in addition to stomach problems; head and muscle aches with fatigue; rash or skin problems; watery, itchy, or burning eyes; allergies; and other symptoms. Repeat interviews were conducted for approximately 5% of absences for quality-control purposes.

Each illness-related absence was classified as respiratory or nonrespiratory on the basis of the reported symptoms. We defined a respiratory illness as an illness that included one or more of the following symptoms: runny nose/sneezing, sore throat, cough (any, wet, or dry), earache, wheezing, or asthma attack. Respiratory absences were further classified into non-mutually exclusive categories of upper respiratory illness and/or as one of two types of lower respiratory illness (LRI): LRI with wet cough or LRI with wet cough/wheeze/asthma. We defined an upper respiratory illness as a respiratory illness with one or more of the following symptoms: runny nose/sneezing, sore throat, and earache. GI illnesses included illnesses with "stomach problems" such as vomiting and diarrhea as one of the reported symptoms.

Absence Incidence Rates

We categorized each absence day as an incident or prevalent absence day using absence reports and school calendars to identify the days each school was in session. We defined an incident absence as an absence that followed attendance on the preceding school day. We defined a prevalent absence day as an absence that occurred after an absence on the preceding school day. The date of an absence occurrence was assigned to the incident day of each series of absence days.

We used the daily number of incident absences in each community and the corresponding daily number of children at risk for an absence in each community to calculate daily community-specific incident absence rates. We defined the number of students attending a school as the number of participants enrolled in a school on a day that the school was in session less the number of prevalent absences. We calculated daily community-specific incidence rates of absence by pooling the data from the reporting schools in each community and dividing the community-specific number of incident absences by the number of students attending schools in that community on the day of interest. The average incidence rate for school absences was computed for each community by averaging daily rates and for the entire cohort by averaging across days and communities. Stratified rates (for example, by asthma status) were calculated by identifying the number of absences and number of students at risk within each stratum and calculating daily community-specific rates and average rates as described.

On the basis of data collected by the active surveillance system, absences were divided into three mutually exclusive outcomes: non-illness-related absences, illness-related absences, and absences of unknown type (due to failure to obtain necessary classification information). Because some absences were of unknown type, the type-specific absence incidence rates were adjusted for ascertainment failure. To adjust the type-specific incident absence rates, we calculated a daily community-specific information success ratio, which we defined as the daily proportion of timely absence reports in each community for which sufficient information was obtained to assign the absence as illness related or non-illness related. This success ratio was then smoothed over time using a very rough smoother (using 10 degrees of freedom). The smoothing was intended to reduce the random fluctuation due to the limited number of events on each day within a community but in such a way that it did not substantially alter the overall trend in the data or the observed values. A symptom-specific incidence rate corrected for ascertainment is of the form: (number of incident cases)/(number at risk × smoothed success ratio).

Assessment of Air Pollution Levels

Levels for O_3, PM_{10}, and NO_2 were measured continuously with hourly averaging at central-site monitors in each of the 12 communities.[18] We calculated the daily 1-hour maximum O_3, the 24-hour average of O_3, and the 10 am–6 pm average of O_3, as well as the 24-hour averages of PM_{10} and NO_2. We focused on the 10 am–6 pm average of O_3 because it is an index of exposure during the temporal peak of ozone and outdoor activity. The 24-hour averages of PM_{10} and NO_2 were used because they lack the temporal peak exhibited by O_3. The monitoring program also reported daily 24-hour average, 24-hour maximum, and 24-hour minimum temperatures at each of the 12 monitoring locations. To assess the effects of long-term average levels of O_3, PM_{10}, and NO_2 on acute effects, we divided communities into high and low groups for each pollutant on the basis of its ranking on average levels for 1995. The high and low groups included the same communities for PM_{10} and NO_2.

Statistical Methods

To examine acute effects of each air pollutant on the rate of absences, we fitted a two-stage time-series model to the absence count data.[19–23] Letting $\mu_c(t)$ denote the expectation of these absence counts and $R_c(t)$ denote the number of children at risk in community c on day t, the first-stage Poisson log-linear model has the form

$$\text{Stage 1: } \ln[\mu_c(t)] = \ln(R_c(t)) + s(t) + b_c + d_c[X_c(t) - X_c] + \gamma Z_c(t)$$

where b_c denotes the average absence rate in community c, adjusted for the effects of time-dependent covariates $Z_c(t)$ (for example, temperature, day of the week), and d_c is the within-community slope of the regression of change in daily absence rates with change in daily pollution $X_c(t)$ centered at the 6-month average for the study period X_c. The centering assumes a log-linear relation between the pollutants and absences. Here, $s(t)$ denotes a smooth function of time to account properly for autocorrelation and long- and short-term time trends in the multiple time series of counts. We use 5 degrees of freedom for the 6-month period to remove any temporal cycles of up to 2 weeks.[20] The first-stage model was also adjusted for day of the week (with Friday as the reference day) and temperature (24-hour average, daily minimum, and daily maximum). The offset term, $R_c(t)$, in the Poisson model was adjusted by using a smoothed version of the success ratio as described above.

Because the effects of pollutant exposure on a given day are likely to occur over several days, we fit models that allowed acute effects to be distributed over time. To account for a lag structure of the pollution effect, we modified the first-stage model by including community-specific polynomial distributed lag terms[24–27] leading to a model of the form:

$$\ln[\mu_c(t)] = \ln[R_c(t)] + s(t) + b_c + \gamma Z_c(t) + \Sigma_k g_{ck} \Sigma_j [X_c(t-j) - X_c] j^k$$

where $j = 1, ..., L$, $d_{cj} = \Sigma_k g_{ck} j^k$, and $k = 0, ..., D$, implying that the effects of each of the previous L days are distributed over subsequent days following a polynomial function of degree D. Appropriate values for L and D are optimally selected by comparing the Akaike Information Criterion[22,28] of the models based on a grid of L and D values assuming the same D and L values for all communities. This assumption is based on biological considerations indicating that the effects of pollutants should have the same lag structure in different communities in the Los Angeles region. The quantity $d_{cj} = \Sigma_k g_{ck} j^k$ is then interpretable as the polynomially smoothed estimate of the effect of air pollution on lagged j days, and their sum $d_c = \Sigma_j d_{cj}$ is the overall effect of pollution over the entire lag period. The estimates of d_{cj} and their variance estimates are then recovered through the explicit relation between d_{cj} and g_{ck}.[26]

The first-stage regression is followed by an ecologic linear regression model given by:

$$\text{Stage 2: } d_c = \delta_0 + \delta X_c + \eta_c$$

The stage 2 regression takes the sum of the lagged community-specific effects, d_c, and the appropriate variance estimates from stage 1. The parameter δ_0, the mean of the within-community slopes d_c, serves as an aggregated acute-effect estimate and is the quantity of primary interest for testing acute effects of air pollutants. Because long-term pollution levels may affect responses to acute changes in exposure level, the stage 2 model includes long-term average levels of any of the pollutants of interest and allows modification of the community-specific slopes for the acute effects by long-term average pollution levels. The parameter δ characterizes the modifying effect of the long-term average pollution levels on the relation between change in absences and change in daily within-community pollution levels. Note that we use the deviation of the daily exposure values, $X_c(t)$, from X_c in the first-stage model to make the within- and between-community comparisons of pollution effects independent. The second-stage "ecologic" regression is weighted by the inverses of the variances of d_c.

Using this framework, we fitted separate models for three pollutants; O_3 (24-hour average, daily maximum, and 10 am–6 pm daily average), PM_{10} (24-hour average), and NO_2 (24-hour average). To account for effects of long-term ambient pollutant levels, regression models were fitted and the overall summary of acute effect of a pollutant across communities was estimated, adjusted for the 1995 community-specific average levels of a pollutant. The estimate of δ_0 provides an overall summary of the acute effects from January through June 1996, adjusted for 1995 average levels of pollution or any other community-specific ecologic factor.

To assess further whether long-term average pollutant levels modify the acute effects of a pollutant, stratified models were fit using categories of high- and low-pollution communities. For any given number of strata, S, the stage 2 model becomes $d_c = \delta_{0s} + \eta_c$, where $s = 1, \ldots S$ and summary estimates are obtained as above. Strata of communities were formed on the basis of rankings using 1995 average pollution levels. We divided communities into high and low based on long-term average levels of O_3 and PM_{10} or NO_2.

Results

The distribution of sociodemographic characteristics, medical conditions, ETS exposure, and outdoor activity varied among the communities (Table 1). The average daily incidence rate for all types of absences combined was 3.07 per 100 student-days based on an average daily attendance of 1,502 students (Table 2). Average daily absence rates were highest in Lake Gregory and lowest in Upland. Although the method of absence reporting by schools varied by community (Table 1), the method of school attendance reporting did not appear to have a large influence on incidence rates.

The subset of absences that was reported in a timely enough manner to be eligible for the active surveillance system was an unbiased sample of absences occurring on all days (Table 2). The distribution of determinants of absences and the average daily rates for all types of absences on days that were reported within 4 weeks did not differ substantially from the distribution and average rates on days ascertained over the period of study. The crude average daily rates per 100 participants were 1.07 for non-illness-related absences, 1.34 for illness-related absences, and 0.61 for absences of unknown type (Table 3). The daily information success ratio averaged 0.81, and exceeded 0.72, for all subgroups.

The ascertainment-adjusted daily rate for illness-related absences was higher than for non-illness-related absences for all participants combined (Table 4). Lake Gregory had the highest adjusted daily rate for illness-related absences, and Long Beach had the lowest rate. Illness-related absences were primarily due to respiratory illnesses, most of which had upper respiratory symptoms (Table 4). Adjusted daily rates of absences for respiratory illness, upper respiratory illness, LRI with wet cough/wheeze/asthma, and LRI with wet cough varied among communities and among ethnic and education groups. Rates of absences for respiratory illness and upper respiratory illness were twice as high in Lake Gregory compared with rates in Long Beach. Children with asthma, wheezing, and ETS exposure had higher absence rates for all categories of respiratory illness than children without asthma, wheezing, or ETS exposure. Adjusted absence rates for GI illness did not vary as substantially as rates for respiratory illness by children's asthma status, wheezing status, or ETS exposure (Table 4). Absences

TABLE 1. Percentage Distributions of Sociodemographic Characteristics and Selected Medical History and Exposures among Participants, Air Pollution, and Absence Study, January through June 1996

			Race/Ethnicity					Parent Education*					Conditions				Reporting Method†	
Community Reporting	N	Males	White	Hispanic	African American	Asian	Other Race	<12th Grade	12th Grade	Some College/ Technical School	4 Years College	Postgraduate	Asthma	Wheeze	ETS	Outdoor Activity >11.25 Hours	Subject-Specific Reporting	Whole Grade
Alpine	177	49.7	73.4	20.9	0	0.6	4.5	7.9	20.3	49.2	10.7	9.0	13.6	33.9	16.4	57.6	0	100.0
Lake Elsinore	171	47.4	52.0	33.9	2.3	2.9	6.4	18.1	21.1	38.0	11.1	4.1	11.1	31.6	21.1	45.0	45.6	54.4
Lake Gregory	164	52.4	71.3	22.0	0.6	0	5.5	9.8	19.5	50.6	7.3	8.5	14.6	35.4	29.9	29.9	24.4	75.6
Lancaster	176	47.2	49.4	31.3	10.8	2.3	5.1	17.6	18.2	44.9	6.8	8.0	16.5	34.7	24.4	52.3	100.0	0
Lompoc	166	49.4	44.0	36.1	6.6	9.0	4.2	12.7	19.3	48.8	9.6	5.4	10.8	29.5	19.9	33.1	34.3	65.7
Long Beach	158	54.4	32.3	23.4	21.5	13.9	8.2	10.8	19.6	39.2	13.3	12.0	13.9	27.8	20.3	38.0	66.5	33.5
Mira Loma	152	48.0	40.8	52.6	2.0	1.3	2.6	27.0	24.3	31.6	7.9	1.3	14.5	34.2	24.3	42.8	100.0	0
Riverside	152	49.3	40.1	40.8	10.5	1.3	5.9	15.1	23.0	32.9	9.2	17.1	11.8	26.3	12.5	52.6	0	100.0
San Dimas	162	48.8	48.8	35.2	1.9	8.6	5.6	6.2	15.4	53.7	10.5	9.3	18.5	30.9	17.3	38.9	0	100.0
Atascadero	157	56.1	72.6	17.2	1.9	1.3	7.0	4.5	17.8	50.3	8.9	17.2	19.7	43.3	13.4	50.3	0	100.0
Santa Maria	156	49.4	22.4	62.8	0.6	7.1	3.2	21.2	22.4	30.8	7.1	5.1	12.2	19.2	12.8	34.6	100.0	0
Upland	144	47.2	66.7	17.4	4.2	7.6	4.2	2.1	7.6	46.5	22.9	20.8	11.8	27.8	8.3	34.0	100.0	0
Total	1,935	49.9	51.4	32.7	5.2	4.6	5.2	12.8	19.1	43.2	10.3	9.7	14.1	31.3	18.6	42.6	46.9	53.1

ETS = environmental tobacco smoke.
* Refers to parent/guardian who completed the subject's baseline questionnaire.
† Reporting methods included schools that provided lists of whole grades and those that provided study subject-specific reports.

due to GI illness showed a different pattern among ethnic groups and communities from that of respiratory illnesses, with Alpine having approximately 2.5-fold higher rates than Santa Maria and Long Beach.

Air Pollution

The patterns of O_3, NO_2, and PM_{10} varied markedly within and among the communities (Figure 1). The average 10 am–6 pm ozone was highest in Riverside and lowest in Long Beach. The communities with the largest daily variations were Mira Loma, Riverside, and San Dimas, with daily levels ranging from lower than the levels observed in unpolluted regions to greater than 150 ppb.

The 24-hour average PM_{10} varied by approximately the same magnitude as O_3; however, several of the towns with the higher O_3 had lower PM_{10} (Figure 1). Mira Loma had the highest level and largest range in 24-hour average PM_{10}, and several communities had median levels below 20 $\mu g/m^3$. The 24-hour average NO_2 levels varied among the communities, and some communities (Lake Gregory and Lompoc) had very low levels (Figure 1). Long Beach, which had low O_3, had comparatively high NO_2. Lompoc, Santa Maria, and Atascadero had lower levels of all three of the pollutants of interest. The communities showed a large range of long-term average pollutant levels on the basis of 1995 pollution levels (Table 5). The same six communities were in the high stratum for both NO_2 and PM_{10}.

Time-Series Regression

We found that a 30-day lag period with a cubic polynomial-constrained distributed lag model best described the data for all absences, non-illness-related absences, and respiratory absences for all three pollutant metrics of interest. A 15-day lag period provided the best fit for upper and lower respiratory absences for all three of the pollutant metrics.

Ozone

Average O_3 for 10 am–6 pm was strongly associated with illness-related absences and especially respiratory absences. The summary estimates of the percentage increase in absence rates associated with O_3 on each of the 30 lag days are shown scaled to a 20-ppb change in O_3, a change that is less than the smallest range in any of the 12 communities during the 6-month period of study (Figure 2). The acute effects of O_3 were increased at a 3-day lag, peaked at a 5-day lag, and subsequently showed a slow decrease. Overall estimates of the effect of acute change in O_3 on absences are obtained by summing the area under the distributed lag curve over the 30-day lag period. Daily 1-hour peak O_3 produced the same overall results as analyses using the 10 am–6 pm average O_3.

A 20-ppb increase in O_3 was associated with a 62.9% absence rate increase for illness, 82.9% increase for respiratory illnesses, 45.1% increase for upper respiratory illnesses, 173.9% increase for LRI with wet cough, and

TABLE 2. Average Daily Absence Incidence Rates per 100 Children-Days and Average Number of Children at Risk per Day on All Days and Days with Active Surveillance for Type of Absence by Selected Participant Characteristics, Air Pollution and Absence Study, January through June 1996

	All Days			Active Surveillance Days		
	Absence Rate/100	Average No. Children at Risk/Day	%	Absence Rate/100	Average No. Children at Risk/Day	%
All	3.07	1,502.2	100.0	3.02	996.4	100.0
Sex						
Females	3.08	751.2	50.0	3.10	500.9	50.3
Males	3.06	751.0	50.0	2.93	495.4	49.7
Ethnicity/race						
Missing	2.40	12.5	0.8	2.04	8.0	0.8
White, non-Hispanic	3.13	776.5	51.7	3.10	498.7	50.1
Hispanic	3.16	483.1	32.2	3.20	327.6	32.9
Black (African-American)	1.84	82.0	5.5	2.02	61.7	6.2
Asian/Pacific Isle	2.00	71.2	4.7	1.29	50.2	5.0
Other	3.62	78.1	5.2	3.89	51.0	5.1
Education of signer						
Missing	3.14	71.2	4.7	2.97	45.1	4.5
<12th grade	3.59	182.5	12.1	3.73	124.9	12.5
12th grade	3.25	287.2	19.1	3.19	189.9	19.1
Some college/technical school	3.16	651.4	43.4	3.05	426.9	42.8
4 years of college	2.45	159.2	10.6	2.96	110.0	11.0
Postgraduate	2.39	150.8	10.0	2.35	99.9	10.0
Community						
Alpine	3.23	158.6	10.6	3.22	116.0	11.6
Lake Elsinore	3.78	109.3	7.3	3.82	93.6	9.4
Lake Gregory	4.34	129.1	8.6	4.36	105.3	10.6
Lancaster	3.06	128.4	8.5	3.10	90.3	9.1
Lompoc	2.84	151.4	10.1	3.17	106.1	10.7
Long Beach	2.35	149.7	10.0	2.37	124.2	12.5
Mira Loma	3.30	149.5	10.0	3.35	143.1	14.4
Riverside	2.97	151.5	10.1	2.94	143.8	14.4
San Dimas	2.80	159.7	10.6	2.50	86.0	8.6
Atascadero	2.82	134.6	9.0	3.06	103.7	10.4
Santa Maria	2.83	112.9	7.5	2.57	83.0	8.3
Upland	2.29	143.0	9.5	2.36	114.6	11.5
Diagnosed asthma						
Missing	3.15	45.4	3.0	3.24	30.5	3.1
No	2.98	1,243.3	82.8	2.94	827.1	83.0
Yes	3.65	213.5	14.2	3.61	138.7	13.9
Reported wheeze						
Missing	2.55	89.6	6.0	2.73	61.3	6.2
No	2.88	943.2	62.8	2.81	630.2	63.2
Yes	3.55	469.4	31.2	3.55	304.9	30.6
Any ETS						
Missing	3.17	49.7	3.3	3.02	32.8	3.3
No	2.93	1,181.0	78.6	2.86	786.4	78.9
Yes	3.67	271.5	18.1	3.72	177.2	17.8
7-day outdoor activities						
Missing	3.66	174.2	11.6	3.61	117.2	11.8
≤11.25 hours	3.04	863.3	57.5	3.03	580.0	58.2
>11.25 hours	3.10	638.9	42.5	3.00	416.4	41.8
School report method						
Whole grade	3.19	793.4	52.8	3.03	464.0	46.6
Participants	3.12	721.2	48.0	3.08	545.8	54.8

ETS = environmental tobacco smoke.

68.4% increase for LRI with wet cough/wheeze/asthma (Table 6). To determine the sensitivity of our estimates to the amount of smoothing used to remove seasonal variation, we refitted the models using 3 degrees of freedom and found that the estimates were essentially unchanged. For example, the effect of ozone on respiratory absences changed from an 82.9% increase to an 81.3% increase. Ozone-related increases in all absences and illness-related absences were larger in communities with lower levels of NO_2 or PM_{10} than in communities with higher levels of NO_2 or PM_{10} (Table 7). The acute effects of O_3 on respiratory illness-related absenteeism were also larger in communities with lower long-term average PM_{10} (454.9%) compared with communities with high average PM_{10} (42.9%).

PM_{10} AND NO_2

Daily 24-hour PM_{10} was associated with all absences (Table 6). However, increased daily PM_{10} was only associated with increases in non-illness-related absences. A change of 10 $\mu g/m^3$ in PM_{10} was associated with a 22.8% increase in all types of school absences combined and with a 97.7% increase in non-illness-related ab-

TABLE 3. Average Crude Daily Absence Incidence Rates per 100 Children-Days and Performance Characteristics of the Active Surveillance System by Selected Participant Characteristics, Air Pollution and Absence Study, January to June 1996

	Absence Rate/100			Information Success	
	Crude Non-Illness	Crude Any Illness	Unknown Type	Mean Success Ratio	Range
All	1.07	1.34	0.61	0.81	0.70–0.99
Sex					
Females	1.10	1.40	0.59	0.81	0.68–0.99
Males	1.05	1.27	0.61	0.81	0.65–0.99
Ethnicity/race					
Missing	1.25	0.07	0.73	0.72	0.57–0.93
White/non-Hispanic	1.03	1.42	0.65	0.82	0.70–0.99
Hispanic	1.15	1.35	0.70	0.81	0.57–0.99
Black (African-American)	1.05	0.71	0.26	0.81	0.59–0.93
Asian/Pacific Isle	0.39	0.81	0.10	0.82	0.67–0.94
Other	1.66	1.65	0.58	0.81	0.43–1.01
Education of signer					
Missing	1.01	1.20	0.76	0.81	0.56–0.96
<12th grade	1.46	1.37	0.89	0.80	0.49–0.91
12th grade	1.08	1.56	0.55	0.80	0.44–0.92
Some college/technical school	1.09	1.36	0.60	0.82	0.69–0.99
4 years of college	1.33	1.23	0.40	0.82	0.56–0.94
Postgraduate	0.67	1.20	0.47	0.81	0.54–0.97
Community					
Alpine	0.92	1.43	0.87	0.75	0.57–1.00
Lake Elsinore	1.34	1.80	0.67	0.84	0.44–1.02
Lake Gregory	1.47	1.83	1.06	0.76	0.54–0.94
Lancaster	1.14	1.24	0.73	0.82	0.67–1.02
Lompoc	0.88	1.74	0.55	0.83	0.66–0.99
Long Beach	1.16	0.81	0.40	0.85	0.75–0.97
Mira Loma	1.20	1.58	0.56	0.82	0.72–0.89
Riverside	0.87	1.37	0.69	0.76	0.55–0.90
San Dimas	0.78	1.19	0.52	0.82	0.69–0.92
Atascadero	1.01	1.32	0.72	0.80	0.30–0.96
Santa Maria	0.77	1.29	0.51	0.81	0.57–0.95
Upland	0.79	1.19	0.37	0.86	0.74–0.99
Diagnosed asthma					
Missing	1.44	1.19	0.61	0.81	0.58–0.95
No	1.08	1.26	0.60	0.81	0.70–0.99
Yes	1.02	1.88	0.71	0.81	0.61–0.97
Reported wheeze					
Missing	0.90	0.88	0.95	0.80	0.61–0.95
No	1.03	1.23	0.55	0.81	0.70–0.99
Yes	1.24	1.68	0.63	0.81	0.65–0.97
Any ETS					
Missing	1.37	0.98	0.68	0.79	0.44–0.94
No	1.00	1.28	0.59	0.81	0.70–0.99
Yes	1.29	1.79	0.65	0.81	0.65–0.95
7-day outdoor activities					
Missing	1.32	1.57	0.71	0.82	0.62–0.99
≤11.25 hours	1.10	1.35	0.58	0.81	0.44–0.99
>11.25 hours	1.05	1.36	0.58	0.81	0.65–0.90
School report method					
Whole grade	1.15	1.22	0.66	0.79	0.56–0.91
Participants	1.08	1.41	0.58	0.83	0.70–0.99

ETS = environmental tobacco smoke.

sences, but a 5.7% increase in illness-related absences. Daily PM_{10} was not materially associated with any of the categories of respiratory illness-related absences. NO_2 had only a weak association with school absenteeism (Table 6).

Discussion

We found that day-to-day changes in O_3 were associated with a substantial increase in school absences from both upper and lower respiratory illnesses. Absences were increased 2–3 days after exposure and reached a peak on day 5 after exposure. The short-term effects of O_3 on respiratory illness-related absences are consistent with a large body of evidence on the acute adverse effects of O_3 on children's respiratory health.[3] Exposure to O_3 is known to be associated with increased hospital admissions for respiratory infections among children. Hospital admission ranks as a severe outcome in the range of adverse effects, and most respiratory illnesses do not lead to hospital admission for treatment. School absences due to respiratory illnesses may usefully represent the first tier of adverse effects that are far more common than severe adverse effects.

A limited number of studies have examined the relation between O_3 exposure and school absenteeism. In a study in Mexico City of 111 preschool children, O_3 was associated with higher rates of absenteeism due to respiratory illnesses.[29] Children exposed to more than 130 ppb of O_3 on 2 consecutive days had a 20% increase in the occurrence of preschool-reported respiratory ill-

TABLE 4. Type-Specific Adjusted* Absence Incidence Rates per 100 Children-Days by Selected Participant Characteristics, Air Pollution and Absence Study, January through June 1996

	Adjusted Non-Illness	Adjusted Any Illness	Adjusted Non-Respiratory	Adjusted Respiratory	Adjusted Upper Respiratory	Adjusted Lower Respiratory with Wet Cough	Adjusted Lower Respiratory with Wheeze	Adjusted GI Symptoms
All	1.34	1.64	0.60	1.04	0.93	0.18	0.30	0.63
Sex								
Females	1.36	1.71	0.62	1.09	1.00	0.19	0.30	0.65
Males	1.31	1.56	0.59	0.97	0.86	0.18	0.30	0.61
Ethnicity/race								
Missing	1.71	0.10	0.00	0.10	0.10	0.00	0.00	0.00
White/non-Hispanic	1.27	1.73	0.67	1.06	0.98	0.21	0.33	0.75
Hispanic	1.40	1.65	0.57	1.08	0.98	0.19	0.26	0.57
Black (African-American)	1.35	0.86	0.10	0.75	0.68	0.13	0.47	0.21
Asian/Pacific Isle	0.45	1.00	0.21	0.79	0.68	0.10	0.17	0.14
Other	2.11	2.01	0.89	1.13	1.01	0.25	0.34	0.82
Education of signer								
Missing	1.27	1.49	0.87	0.63	0.58	0.13	0.17	0.76
<12th grade	1.79	1.66	0.44	1.22	0.93	0.21	0.44	0.50
12th grade	1.35	1.90	0.75	1.15	1.01	0.19	0.33	0.70
Some college/technical school	1.35	1.67	0.59	1.07	0.97	0.18	0.31	0.65
4 years of college	1.76	1.47	0.37	1.10	0.99	0.14	0.38	0.48
Postgraduate	0.82	1.46	0.45	1.01	1.01	0.28	0.29	0.63
Community								
Alpine	1.20	1.90	0.91	1.00	0.85	0.19	0.26	0.98
Lake Elsinore	1.67	2.08	0.76	1.32	1.17	0.28	0.56	0.90
Lake Gregory	1.90	2.28	0.88	1.41	1.29	0.30	0.35	0.88
Lancaster	1.42	1.47	0.49	0.98	0.91	0.12	0.24	0.64
Lompoc	1.08	2.09	0.71	1.38	1.24	0.24	0.30	0.73
Long Beach	1.36	0.96	0.24	0.72	0.61	0.21	0.31	0.35
Mira Loma	1.48	1.92	0.86	1.06	0.89	0.24	0.41	0.77
Riverside	1.20	1.82	0.72	1.09	1.06	0.20	0.31	0.85
San Dimas	0.94	1.44	0.31	1.13	0.94	0.16	0.36	0.38
Atascadero	1.27	1.61	0.83	0.78	0.60	0.11	0.28	0.66
Santa Maria	0.93	1.62	0.57	1.05	1.04	0.14	0.24	0.40
Upland	0.92	1.38	0.48	0.90	0.84	0.13	0.26	0.55
Diagnosed asthma								
Missing	1.78	1.49	0.51	0.98	0.91	0.35	0.42	0.63
No	1.34	1.54	0.59	0.95	0.89	0.16	0.20	0.61
Yes	1.25	2.28	0.70	1.58	1.25	0.30	0.89	0.76
Reported wheeze								
Missing	1.15	1.06	0.36	0.70	0.67	0.09	0.11	0.49
No	1.28	1.51	0.63	0.88	0.82	0.14	0.17	0.61
Yes	1.53	2.05	0.61	1.44	1.24	0.28	0.59	0.68
Any ETS								
Missing	1.86	1.23	0.68	0.54	0.40	0.07	0.19	0.64
No	1.22	1.56	0.55	1.01	0.92	0.18	0.28	0.59
Yes	1.62	2.17	0.83	1.35	1.21	0.23	0.46	0.82
7-day outdoor activities								
Missing	1.60	1.93	0.80	1.14	1.08	0.21	0.28	0.79
≤11.25 hours	1.38	1.65	0.63	1.03	0.92	0.18	0.28	0.63
>11.25 hours	1.30	1.66	0.58	1.08	0.97	0.18	0.34	0.64
School report method								
Whole grade	1.45	1.55	0.52	1.03	0.91	0.20	0.31	0.64
Participants	1.33	1.69	0.61	1.08	0.98	0.19	0.32	0.60

GI = gastrointestinal; ETS = environmental tobacco smoke.
* Adjusted for interview failure using the success ratio as described in the methods section.

nesses. Studies of school absenteeism in California failed to find an association with oxidants or other pollutants, but these studies did not assess the effects of daily changes in pollutant levels on respiratory absences.[30] The relations between other air pollutants, such as SO_2, and school absences have also been investigated; however, the effects of O_3 were not examined, because levels were considered too low to have adverse effects.[31] We lack data to investigate further the reasons for the smaller effect of acute changes in O_3 on respiratory illness-related absences in communities with high long-term average PM_{10} levels. One possible explanation is seasonal attenuation of children's responses to air pollution. Seasonal attenuation of the acute lung function response to O_3 exposure during high-pollution months has been reported, suggesting that long-term exposure to elevated levels of PM can affect acute response to O_3.[32,33]

The association of daily 24-hour average PM_{10} with all absences in this study was primarily due to a relation with non-illness-related absences. The small association with illness-related absences was unexpected, because studies have shown that particulate pollution is associated with reduction in lung function, increased rates of acute bronchitis in children, increased incidence of respiratory symptoms, increased emergency room visits and hospitalizations for respiratory disease, and increased mortality.[5,17,34,35] Our study is consistent with a report by Ransom and Pope,[36] who studied the relation between school absenteeism and PM_{10} in Utah Valley for 6 years between 1985 and 1990, using weekly absenteeism data

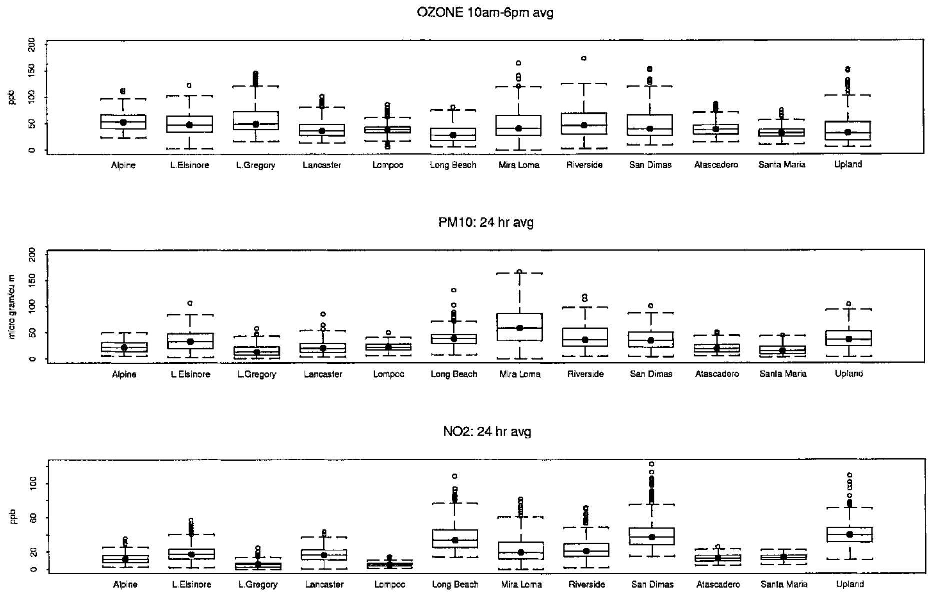

FIGURE 1. Boxplots of 10 am–6 pm average O_3, 24-hour average NO_2, and 24-hour average PM_{10} in study communities (Air Pollution and Absence Study, January 1 through June 30, 1996). In the box plots, the median, first quartile, and third quartiles form the box, and the whiskers depict $\pm 1.5 \times$ interquartile range. Any other extreme values outside of the whiskers are plotted individually.

from one school district and daily data from one elementary school. They observed that a 100 $\mu g/m^3$ increase in the 28-day moving average of PM_{10} was associated with a 40% increase in overall absences and that the effect was larger in younger children. The study did not, however, distinguish between illness and non-illness-related absenteeism. We were unable to investigate directly non-illness absences, because we did not ask about reasons for non-illness absences during interviews. We considered a number of potential sources of bias, such as incomplete control of temporal trends and the effects of temperature and differences in the effects among the communities, by conducting sensitivity analyses. We found the relations were consistent between communities and robust regardless of adjustments for temporal trends and temperature.

Acute effects of NO_2 on school absenteeism were not observed at the levels measured in communities during the period of study. Although NO_2 exposure may be associated with respiratory symptoms, little evidence exists that symptoms from NO_2 exposure result in school absences.[2,4,37] In a study of the relation between air pollution and absenteeism in Helsinki, Ponka[38] reported that mean weekly NO_2 concentrations were associated with absenteeism among adults; however, low ambient temperature accounted for the associations with absences among children in day care centers and school children.[38] In the present study, the lack of association may also reflect the narrow range of NO_2 exposure and possible exposure misclassification due to the use of a central site monitor to assign exposure levels. Misclassification of exposure is likely to be the same on different days within each community, suggesting that misclassification is likely to be nondifferential.[39]

In preliminary analyses, we used a bidirectional case-crossover approach to assess the air pollution and absence relation; however, the time-series analysis provides an analytic framework that efficiently uses all available information and does not have some of the conceptual drawbacks of the case-crossover approach.[40–43] The distributed lag model constrained the

TABLE 5. Annual Average Air Pollution and Community Rankings for Ozone (O_3), Nitrogen Dioxide (NO_2), and Respirable Particles (PM_{10}) Based on 1995 Levels, Children's Health Study, 1995

Community	Annual Mean 10 am–6 pm O_3 (ppb)	Rank	Annual Mean Daily NO_2 (ppb)	Rank	Annual Mean Daily PM_{10} ($\mu g/m^3$)	Rank	Stratum* (O_3, PM_{10}/NO_2)
Santa Maria	31	1	12	3	20	2	LL
Long Beach	33	2	37	10	39	9	LH
Atascadero	43	3	13	4	22	4	LL
Lompoc	45	4	5	1	15	1	LL
Lancaster	48	5	19	6	24	5	LL
Mira Loma	54	6	23	8	65	12	LH
Upland	55	7	45	12	45	11	HH
Lake Elsinore	57	8	20	7	35	7	HH
Alpine	58	9	13	5	24	6	HL
San Dimas	60	10	44	11	37	8	HH
Riverside	62	11	25	9	44	10	HH
Lake Gregory	65	12	7	2	21	3	HL

* Strata were defined by ranking communities on 1995 average pollution levels and dichotomizing communities into high (H) and low (L) groups. LL = low O_3 and low PM_{10} or NO_2, LH = low O_3 and high PM_{10} or NO_2, HL = high O_3 and low PM_{10} or NO_2, and HH = high O_3 and high PM_{10} or NO_2.

TABLE 6. Short-Term Effects of 10 am–6 pm Average Ozone (O_3), 24-Hour Average Respirable Particles (PM_{10}) and 24-Hour Average Nitrogen Dioxide (NO_2) on School Absence Incidence Rates [Percentage Change and 95% Confidence Limits (CL)], Air Pollution and Absence Study, January through June 1996*

	Pollutant					
	O_3		PM_{10}		NO_2	
Type of Absence	% Change	95% CL	% Change	95% CL	% Change	95% CL
All absences	16.3	−2.6, 38.9	22.8	11.6, 35.2	3.4	−30.6, 54.0
Non-illness	21.2	−12.9, 69.0	97.7	72.6, 126.5	34.6	−43.0, 218.2
Illness	62.9	18.4, 124.1	5.7	−12.1, 27.0	−4.6	−42.4, 57.8
Nonrespiratory	37.3	5.7, 78.3	10.2	−14.6, 42.3	−36.8	−69.5, 30.8
Respiratory†	82.9	3.9, 222.0	−4.3	−32.2, 35.0	19.6	−36.2, 124.4
URI	45.1	21.3, 73.7	5.5	−6.8, 19.4	−7.4	−30.3, 23.0
LRI/wc	173.9	91.3, 292.3	−7.7	−49.2, 67.7	−37.5	−73.9, 49.4
LRI/W/A	68.4	43.4, 97.8	−7.1	−34.1, 30.8	5.1	−60.3, 178.0

URI = upper respiratory illness; LRI = lower respiratory illness; wc = wet cough; W/A = wet cough/wheeze or asthma attack.
* Results are reported for 20 ppb O_3, 10 $\mu g/m^3$ PM_{10}, and 10 ppb NO_2. Models are fitted using community-specific polynomial-distributed lag models (degree 3) with 30-day lag period except URI, LRI/wc$^+$, and LRI/W/A had 15-day lag periods.
† Fifteen-day lag periods used.

acute effects of pollutants to follow a polynomial function of air pollution. Based on an objective criterion for choice of the number of lag days, minimizing the Akaike Information Criterion, a cubic polynomial that included either 15 or 30 lag days, best described the lagged effects. Other choices of the lag period length would produce consistent results for the O_3 effect on respiratory illness-related absences. The 15- to 30-day lag periods for the O_3 effects on respiratory illness-related absences are consistent with data from a number of studies showing that effects of air pollution on respiratory health outcomes may persist for up to 5 weeks.[36,44,45]

Our study enrolled and actively followed more than 2,000 4th-grade school children. The active surveillance system and modeling strategy did, however, have some limitations. Although the restriction of absences to those reported within 1 month of occurrence may have introduced bias into our study, it was adopted to minimize any recall bias of absence events by parents. On the basis of the distributions of the study population in the full and restricted sample of absence days, we found little evidence of any selection bias from the restriction. To account for the effects of incomplete ascertainment, we adjusted the denominator of the rates and the offset in the Poisson time-series models for the proportion of absences with information on absence type. To investigate the robustness of our estimates to the assumptions implicit in this adjustment, we conducted sensitivity analyses by limiting the analyses to those days with greater than 70% ascertainment. Restriction to days with nearly complete information had little effect on the magnitude of the associations. To assess further the potential for bias from the variation in ascertainment, we also examined the relations between the daily pollution and callback rates as well as absence rates and callback rates. We found that the community-specific smooth success ratios showed, in general, a weak negative correlation with ozone. Because ozone was positively correlated with absence rates over the period of study, a negative bias toward the null would be expected and cannot explain our ozone results. The correlations for NO_2 and PM_{10} were generally smaller, making the potential for bias less likely.

We also attempted to examine variation in the relations using models stratified by asthma, ETS exposure, or other sociodemographic factors, but were unsuccessful owing to the short length of time series

TABLE 7. Short-Term Effects of Ozone (O_3) [Percentage Change and 95% Confidence Limits (CL)] on School Absence Incidence Rates, Stratified by Long-Term Average 10 am–6 pm O_3 and 24-Hour Average Respirable Particles (PM_{10}) or Nitrogen Dioxide (NO_2),* Air Pollution and Absence Study, January through June 1996†

	Community Ranking							
	Based on O_3				Based on PM_{10}/NO_2			
	Low O_3		High O_3		Low PM_{10} (NO_2)		High PM_{10} (NO_2)	
Type of Absence	% Change	95% CL	% Change	95% CL	% Change	95% CL	% Change	95% CL
All absences	14.0	−16.7, 56.1	16.2	−5.8, 43.3	68.2	25.9, 124.8	6.4	−7.1, 21.9
Non-illness	17.0	−35.3, 111.9	20.1	−19.2, 78.6	49.8	−30.7, 223.7	13.6	−20.3, 61.8
Illness	87.6	8.3, 225.2	48.8	3.0, 115.0	223.5	90.4, 449.7	38.1	8.5, 75.8
Nonrespiratory	29.9	−19.8, 110.6	31.5	−5.6, 83.0	29.6	−32.2, 147.9	31.3	−2.8, 77.4
Respiratory	136.8	−11.5, 533.1	57.7	−18.1, 203.9	454.9	90.0, 1520.0	42.9	−11.2, 130.1

* High and low strata included the same communities for either PM_{10} or NO_2.
† Results are reported for 20 ppb O_3, 10 $\mu g/m^3$ PM_{10}, and 10 ppb NO_2. Models are fitted using community-specific polynomial-distributed lag models (degree 3) with 30-day lag period.

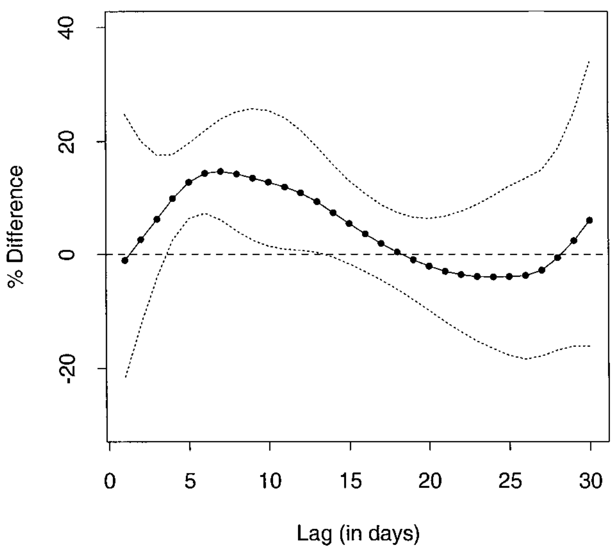

FIGURE 2. Distributed lag estimates and 95% confidence intervals for the effect of 10 am–6 pm O_3 (per 20 ppb) on respiratory illness-related absences (Air Pollution and Absence Study, January 1 through June 30, 1996).

and the low number of events within community-specific strata. Lastly, it was not feasible to examine simultaneously the acute effects of multiple pollutants using the two-stage distributed lag framework developed for this analysis. Future development of a binomial time-series model with a flexible distributed lag structure would provide the framework to include individual-level covariates and multipollutant effects in time-series analyses.

In conclusion, relatively small short-term changes in O_3 were associated with increases in respiratory illness-related school absences in children 9–10 years of age. Because exposures at the levels observed in this study are common, the increase in school absenteeism from respiratory illnesses associated with relatively modest day-to-day changes in O_3 concentration documents an important adverse impact of O_3 on children's health and well-being.

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